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Personalized Preventive-Care Pathways through Integrated Behavioral Analytics

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Abstract

Preventive health care is commonly organized around population-level recommendations, periodic screening, and relatively static risk categories. Although these approaches remain essential, they may not fully capture the changing behavioral conditions through which individual health risks develop between clinical encounters. Advances in mobile sensing, wearable technologies, electronic health records, digital phenotyping, and artificial intelligence now make it possible to observe patterns of physical activity, sedentary behavior, sleep, nutrition, medication-taking routines, physiological signals, and other health-related behaviors with greater temporal resolution. This study examines how integrated behavioral analytics can support personalized preventive-care pathways that identify emerging risk, prioritize modifiable behaviors, deliver context-sensitive interventions, and reassess prevention needs over time.

A structured integrative evidence-synthesis methodology was used to examine contemporary research on digital phenotyping, wearable health technologies, artificial intelligence–supported health promotion, personalized digital interventions, and behavioral risk reduction. Recent evidence demonstrates considerable potential but also substantial fragmentation. A 2025 rapid review of 22 artificial intelligence–based health-promotion studies identified interventions targeting dietary behavior, smoking cessation, physical activity, mental health, and preventive care, with several interventions addressing multiple behavioral domains. A separate systematic evidence map included 109 wearable-technology studies involving older adults and identified benefits related to physical-activity monitoring, timely treatment adjustment, patient-centered care, and health-event detection, while noting limited evaluation of acceptability, costs, safety, and sustained real-world use.

The present paper proposes an Integrated Behavioral Preventive-Care Pathway in which longitudinal behavioral and physiological signals are converted into individualized risk profiles, clinically interpretable prevention priorities, adaptive recommendations, and monitored feedback loops. The model explicitly retains clinician oversight and incorporates uncertainty, privacy, informed consent, interoperability, accessibility, and algorithmic fairness as implementation requirements. Integrated behavioral analytics should therefore be understood as decision support rather than autonomous medical decision-making. When appropriately validated and governed, such systems may move preventive care from occasional generalized advice toward continuous, personalized, and participatory risk reduction.

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1. Introduction

No communicable diseases remain one of the principal challenges facing contemporary health systems. The World Health Organization reported that no communicable diseases caused at least 43 million deaths in 2021, representing approximately 75% of global deaths excluding pandemic-related mortality. Cardiovascular diseases, cancers, chronic respiratory diseases, and diabetes account for much of this burden, while behavioral factors such as physical inactivity, tobacco exposure, unhealthy dietary patterns, and harmful alcohol use contribute substantially to preventable risk. Prevention therefore depends not only on detecting established disease but also on identifying and modifying behaviors and exposures before irreversible clinical deterioration occurs.

Conventional preventive care is often delivered through scheduled consultations, age-based screening recommendations, standardized risk calculators, and general lifestyle counseling. These approaches provide a necessary population-health foundation, but many health-relevant behaviors fluctuate considerably between consultations. Physical activity may decline gradually, sleep disruption may become persistent, dietary patterns may deteriorate, medication routines may become inconsistent, and stress-related behavioral changes may occur long before they are visible through conventional clinical measurements. Digital health technologies create an opportunity to observe some of these changes longitudinally rather than relying exclusively on episodic self-report. WHO's current digital-health strategy emphasizes the use of digital technologies, interoperable data, and evidence-informed decision-making to strengthen equitable health systems and improve health outcomes.

Digital phenotyping provides an important conceptual foundation for this transition. Zhang and colleagues describe behavioral phenotyping as the continuous or repeated analysis of everyday behavioral information derived from smartphones and wearable devices, including physical activity, step count, sleep patterns, device use, and related behavioral signals. Physiological phenotyping can additionally incorporate heart rate, blood pressure, glucose, temperature, and respiratory indicators. These data do not independently diagnose disease, but longitudinal patterns may provide clinically useful context concerning changes in behavior, functional status, and exposure to preventable risk.

Personalization becomes especially important because identical preventive recommendations may produce very different effects across individuals. A sedentary person with irregular sleep and gradually rising glucose may require a different intervention pathway from an individual whose principal risk is tobacco use, medication nonadherence, or dietary instability. Artificial intelligence and behavioral analytics can potentially identify such combinations and adapt the timing, intensity, and content of preventive support. A 2025 JMIR rapid review found AI-supported health-promotion interventions across diet, smoking cessation, physical activity, mental health, and preventive care, with mobile applications, conversational systems, personalized coaching, and behavioral feedback among the approaches examined.

The present study therefore investigates how multiple behavioral signals can be integrated into personalized preventive-care pathways rather than managed as disconnected wellness metrics. Its central proposition is that effective precision prevention requires a continuous sequence connecting measurement, interpretation, risk prioritization, personalized intervention, behavioral feedback, and clinical reassessment. The paper simultaneously recognizes that greater data availability does not automatically create better care. Privacy, data quality, algorithmic bias, interoperability, alert burden, accessibility, user engagement, and uncertainty surrounding individual risk estimates must remain central to implementation. Contemporary digital-health evidence strongly supports human-centered and interoperable systems rather than technologies that attempt to replace clinical judgment.

2. Objectives of the Study

2.1 To Examine Behavioral Analytics as a Preventive Risk-Detection Mechanism

The first objective is to examine how longitudinal behavioral information derived from mobile applications, wearable sensors, electronic health records, and patient-generated information may contribute to earlier recognition of preventable health risk. The study particularly considers physical activity, sedentary behavior, sleep, nutrition, physiological monitoring, medication-related behavior, and engagement with preventive recommendations. Rather than interpreting an isolated measurement as clinically decisive, the analysis emphasizes changes from an individual's usual behavioral pattern.

2.2 To Develop a Personalized Preventive-Care Pathway

The second objective is to develop a conceptual pathway capable of converting integrated behavioral information into meaningful preventive action. This pathway incorporates baseline risk assessment, behavioral profiling, and risk stratification, identification of modifiable priorities, personalized intervention selection, real-time or periodic feedback, and longitudinal reassessment. The framework is designed to support clinician–patient decision-making rather than automated treatment prescription.

2.3 To Identify Requirements for Responsible Implementation

The third objective is to examine the methodological and ethical requirements necessary for behavioral analytics to become a reliable component of preventive medicine. Particular attention is given to data validity, interoperability, informed consent, transparency, privacy, bias, digital exclusion, user burden, model generalizability, and the distinction between population-level predictive accuracy and uncertainty surrounding predictions for an individual patient.

3. Review of Literature

3.1 From Population Prevention to Personalized Prevention

Preventive medicine has traditionally differentiated primary prevention, early detection, and management of established risk or disease. Digital technologies are increasingly expanding these functions by enabling repeated measurement outside formal health-care environments. De la Torre and colleagues describe wearable technologies, mobile applications, connected sensors, and AI-supported interventions as important components of emerging digital preventive medicine, particularly where personalized lifestyle recommendations and repeated monitoring can complement conventional screening and counseling.

The theoretical basis closely resembles the predictive, preventive, personalized, and participatory principles of P4 medicine. Digital phenotyping provides one mechanism through which these principles may become operational because it can combine behavioral, physiological, psychological, and environmental information across time. Zhang and colleagues argue that such data can contribute to earlier risk identification and more dynamic health management, although they emphasize that implementation continues to face major privacy, ethical, technical, and standardization barriers.

The distinction between personalized and merely digital prevention is important. Sending an identical physical-activity message to every user constitutes digital delivery but not substantive personalization. A personalized pathway should account for baseline behavior, risk profile, prior response, preferences, barriers, clinical history, and changing behavioral conditions. This principle is consistent with contemporary AI-supported health-promotion research in which personalized coaching and feedback have emerged as recurring intervention components.

3.2 Wearables, Digital Phenotypes, and Behavioral Risk Signals

Wearable and mobile technologies can generate continuous or near-continuous observations that are difficult to obtain through conventional clinical encounters. Activity trackers can quantify steps, movement intensity, and sedentary periods; sleep sensors can characterize sleep timing and duration; mobile applications can record diet or medication behavior; continuous glucose monitors can reveal glycemic responses; and other devices may capture heart rate or related physiological variables. Digital phenotyping aims to combine these signals into more meaningful descriptions of health-related behavior. Sun and colleagues' 2025 systematic scoping review and evidence map included 109 studies concerning wearable technologies for health promotion and disease prevention among older adults. The review identified potential benefits in patient-centered monitoring, physical-activity assessment, timely treatment modification, and detection of unexpected health events. However, comparatively few studies evaluated acceptability, adherence, user experience, safety, or economic implications, highlighting the difference between technical feasibility and sustainable preventive implementation.

Evidence from multimodal phenotyping illustrates why integration may be more informative than single-sensor measurement. Pai and colleagues combined continuous glucose monitoring, physical-activity monitoring, and meal tracking among adults with or at risk of type 2 diabetes, demonstrating the feasibility of constructing behavioral and metabolic digital biomarkers from several complementary data streams. Such approaches are particularly relevant to preventive care because many chronic-disease risks emerge through interactions among behavior, physiology, and environmental context.

3.3 Adaptive Analytics and Behavior-Change Interventions

Behavioral analytics becomes clinically relevant only when data can be translated into an intervention capable of modifying risk. Artificial intelligence has increasingly been used to provide personalized meal planning, physical-activity coaching, smoking-cessation support, weight-management guidance, and individualized behavioral feedback. Yousefi and colleagues' rapid review included 22 AI-based health-promotion studies; 11 used randomized or nonrandomized trial designs, while other studies used cohort, feasibility, observational, mixed-method, and quasi-experimental approaches.

The review identified statistically significant positive outcomes in several domains, including physical activity, dietary behavior, weight loss, mental-health measures, glycemic control, and systolic blood pressure, although effects were not universal across all studies and outcome measures. This heterogeneity reinforces the need to avoid treating AI as a single standardized intervention. Effectiveness depends on the behavioral target, intervention design, population, duration, underlying data, and quality of user engagement.

Adaptive goals may offer an additional improvement over static recommendations. Personalized systems can potentially modify behavioral goals according to recent performance rather than applying the same target indefinitely. However, adaptive intervention systems require strong validation because repeated personalization based on noisy or biased sensor data may generate inappropriate recommendations. The value of behavioral analytics therefore lies not in maximizing the number of measurements collected but in identifying a small number of sufficiently reliable signals that meaningfully alter preventive decisions.

4. Research Methodology

4.1 Research Design

The present study adopted a structured integrative evidence-synthesis and conceptual framework-development methodology. The design was selected because no original patient dataset was provided and because the research question spans preventive medicine, behavioral science, digital phenotyping, wearable technology, artificial intelligence, and health-system implementation.

Peer-reviewed literature and authoritative guidance available up to August 10, 2026 were considered. Search concepts included personalized preventive care, behavioral analytics, digital phenotyping, precision prevention, wearable health technology, AI health promotion, adaptive behavioral intervention, digital biomarkers, and preventive medicine. Greater interpretive weight was given to systematic reviews, controlled interventions, contemporary digital-health evidence maps, and WHO guidance.

4.2 Behavioral Data Integration Framework

The proposed analytical architecture does not assume that every patient requires every available sensor. Instead, data selection should follow clinical relevance and proportionality.

Table 1: Integrated Behavioral Analytics Framework for Personalized Prevention

Data Domain	Representative Indicators	Preventive Interpretation	Potential Action
Physical activity	Steps, activity minutes, activity intensity	Reduced mobility or inadequate activity	Adaptive movement goals
Sedentary behavior	Continuous sitting periods, inactive time	Cardiometabolic behavioral risk	Sitting interruption strategy
Sleep behavior	Duration, timing, regularity	Recovery and behavioral instability	Sleep-hygiene support

Nutrition	Meal timing, dietary logs, intake patterns	Dietary risk and metabolic exposure	Personalized dietary counseling
Cardiometabolic signals	Heart rate, glucose, blood pressure	Emerging physiological risk	Clinical review or monitoring
Medication behavior	Logged doses, refill behavior	Preventable adherence risk	Reminder or pharmacist intervention
Engagement data	Response to prompts, goal completion	Intervention receptivity	Modify intensity or communication
Clinical information	Diagnoses, laboratory results, medications	Baseline medical risk	Adjust preventive pathway
Contextual information	Work pattern, environment, access barriers	Behavioral feasibility	Tailor intervention delivery

4.3 Analytical Procedure and Ethical Safeguards

The proposed pathway applies six interpretive stages: baseline characterization, longitudinal behavioral monitoring, clinically relevant change detection, risk prioritization, personalized preventive intervention, and reassessment. Behavioral changes should be interpreted relative to individual baselines wherever feasible because absolute population thresholds can overlook meaningful within-person changes.

The framework deliberately excludes fully autonomous clinical decision-making. Behavioral predictions may support a decision to intensify counseling, recommend screening, schedule clinical review, or modify the mode of preventive support, but decisions affecting diagnosis or treatment should remain subject to appropriate professional evaluation.

Privacy is a particularly important consideration because digital phenotyping can involve sensitive physiological, behavioral, psychological, and location-related information. Current literature identifies privacy, data ownership, informed consent, standardization, interoperability, technical quality, digital exclusion, and possible discriminatory effects as key barriers to widespread adoption. Data collection should therefore be limited to information necessary for the preventive purpose, accompanied by transparent consent and appropriate security.

5. Analysis

5.1 Evidence Distribution Across Behavioral Prevention Domains

The 2025 rapid review by Yousefi and colleagues provides a useful indication of where AI-supported health-promotion research has concentrated. Among 22 included studies, 10 addressed dietary behavior, six smoking cessation, four physical activity, three mental health, and three preventive care. Four studies addressed multiple health-promotion domains, meaning these categories are not mutually exclusive.

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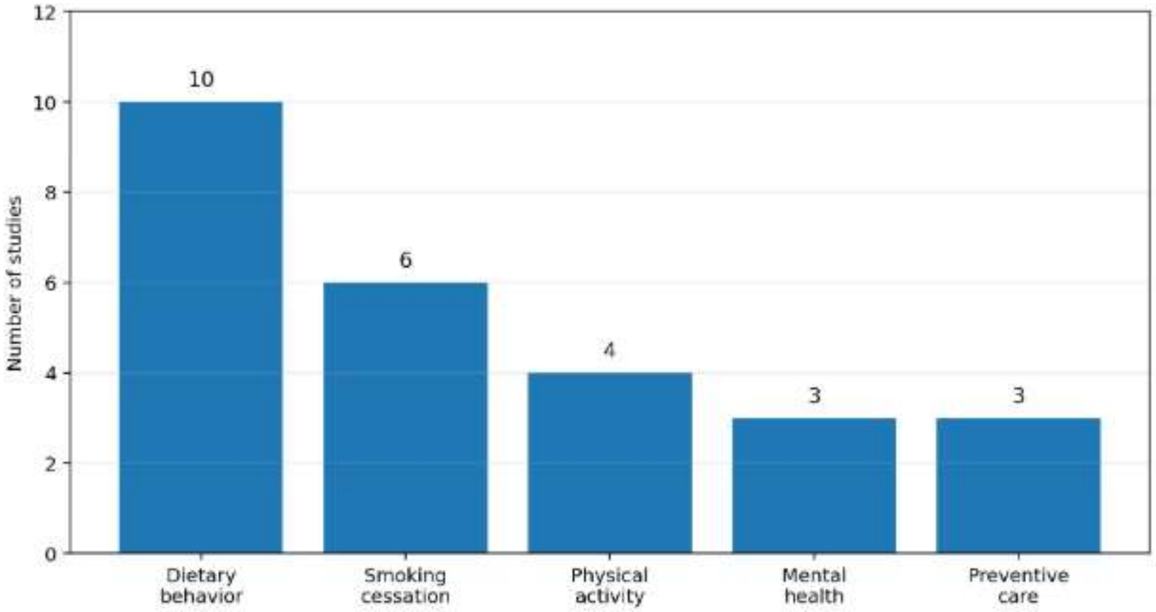
Table 2: Evidence Mapping for Integrated Behavioral Prevention

Preventive Domain	Studies in 2025 Rapid Review	Behavioral Analytics Opportunity
Dietary behavior	10	Personalized intake and meal-pattern feedback
Smoking cessation	6	Trigger identification and adaptive cessation support
Physical activity	4	Activity monitoring and individualized goals
Mental health	3	Behavioral change and distress monitoring
Preventive care	3	Risk alerts and personalized preventive guidance
Multidomain interventions	4	Integration of interacting risk behaviors

5.2 Graphical Evidence Profile

Figure 1: Health-Promotion Domains in AI-Based Intervention Studies



5.3 Proposed Personalized Preventive-Care Pathway

The evidence supports a cyclical rather than one-time preventive-care model:

Baseline Clinical and Behavioral Profile

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Continuous or Periodic Behavioral Monitoring

↓

Detection of Meaningful Behavioral Change

↓

Multidomain Risk Integration

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Personalized Preventive Priority
↓
Context-Appropriate Behavioral Intervention
↓
Patient Feedback and Clinician Review
↓
Outcome Monitoring and Pathway Recalibration

This pathway differs from conventional static risk categorization because the patient's preventive profile is expected to evolve. A period of reduced mobility, disrupted sleep, deteriorating diet quality, or declining intervention engagement may change the priority assigned to preventive actions even when the underlying diagnosis has not changed.

The pathway also separates a behavioral signal from a clinical conclusion. For example, reduced activity detected through a wearable may justify further assessment, but it does not establish whether the cause is illness, injury, workload, weather, device nonuse, or personal preference. The safest implementation is therefore a layered system in which analytics identify patterns requiring attention and clinicians or appropriately designed care protocols determine the response.

6. Discussion

6.1 Moving Prevention from Periodic to Adaptive Care

The central contribution of integrated behavioral analytics is the possibility of making prevention temporally responsive. Traditional preventive encounters offer snapshots of risk. Behavioral sensing can potentially reveal how risk develops between these encounters and whether previously recommended behavior change is actually occurring.

This distinction is important because many preventable risk factors are dynamic. A person may meet physical-activity recommendations during one month and become markedly sedentary during another. A successful dietary intervention may gradually deteriorate, or a smoking-cessation attempt may encounter recurrent behavioral triggers. A personalized preventive pathway can theoretically respond to these changes earlier than a fixed annual review.

The approach aligns with WHO's broader digital-health strategy, which emphasizes translating data and evidence into informed decisions, promoting interoperability, and developing digital systems that strengthen equitable, affordable, and high-quality health services. Personalized preventive care should therefore be integrated into health systems rather than exist only as an isolated consumer-wellness ecosystem.

6.2 Why Integration Is More Valuable Than Isolated Tracking

A single behavioral measurement often has limited meaning. Step count may describe mobility but cannot independently explain cardiovascular risk. Sleep duration may identify disrupted rest but not its underlying cause. Continuous glucose measurements provide metabolic information but become more meaningful when interpreted alongside meals and physical activity.

Multimodal digital phenotyping attempts to overcome this limitation by combining several complementary signals. Existing studies have demonstrated the feasibility of integrating continuous glucose monitoring, activity monitoring, and dietary information, while broader digital-phenotyping research incorporates behavioral, physiological, psychological, and environmental domains.

Integration also enables preventive priorities to compete intelligently for attention. A person does not necessarily benefit from receiving simultaneous recommendations about every measurable behavior. Analytics should identify which modifiable factor is most relevant, feasible, and likely to produce meaningful benefit at a particular time.

This principle may reduce notification fatigue and prevent digital health systems from overwhelming users with excessive recommendations. The objective is therefore minimum sufficient intervention, not maximum possible monitoring.

6.3 Limitations, Equity, and Clinical Governance

The promise of behavioral analytics should not obscure important limitations. Wearable measurements are affected by device characteristics, algorithms, missing data, inconsistent use, sensor placement, and population differences. Sun and colleagues emphasize that algorithm performance depends on datasets, devices, classifiers, and evaluation procedures, while comparatively little research has examined real-world acceptability, costs, safety, and sustained user experience.

A second concern is individual-risk uncertainty. Predictive models are often evaluated according to population-level discrimination or calibration, yet preventive decisions are ultimately made for individuals. Model uncertainty, measurement variability, and differences between development and implementation populations can make individual risk estimates substantially less certain than headline performance metrics suggest. Behavioral analytics should consequently inform rather than dictate preventive care.

Equity presents an additional challenge. Individuals with limited digital access, low digital literacy, unstable internet connectivity, disabilities, or financial constraints may be systematically underrepresented in high-frequency behavioral datasets. Digital phenotyping research also identifies privacy, informed consent, data ownership, unequal access, and discriminatory data use as continuing concerns. A preventive system that performs best for technologically engaged populations could inadvertently widen existing health inequalities.

Clinical governance should therefore require transparent model documentation, subgroup performance assessment, explicit escalation criteria, human review of consequential recommendations, secure data management, mechanisms for correcting inaccurate information, and the ability for individuals to decline or reduce monitoring without losing access to standard care.

7. Conclusion

Integrated behavioral analytics offers a promising pathway for transforming preventive care from generalized and periodic recommendations toward more personalized, adaptive, and participatory risk reduction. Smartphones, wearable devices, clinical records, digital biomarkers, and behavioral interventions increasingly provide the technical capacity to observe health-related patterns outside traditional clinical encounters. Contemporary evidence demonstrates applications across dietary behavior, smoking cessation, physical activity, mental health, metabolic monitoring, and preventive care.

The principal innovation, however, is not continuous data collection itself. The greater value lies in converting clinically relevant behavioral changes into proportionate preventive action. A useful system must determine what information matters, how reliable that information is, whether a change represents meaningful risk, which preventive action is most appropriate, and whether the intervention actually produces improvement.

The proposed model therefore links behavioral monitoring with risk interpretation, personalized intervention, feedback, professional review, and repeated recalibration. It treats AI and behavioral analytics as decision-support mechanisms rather than replacements for clinical reasoning.

Future research should prioritize prospective trials comparing integrated multidomain pathways with conventional preventive care, standardized reporting of behavioral-data quality, longer follow-up, objective health outcomes, cost-effectiveness, equity evaluation, and transparent assessment of algorithmic performance across demographic groups. Wearable and behavioral data should ultimately make preventive care more responsive to people's lives rather than requiring people's lives to conform to technology.

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